Machine Learning Engineer Nanodegree

Supervised Learning

Project 2: Building a Student Intervention System

Welcome to the second project of the Machine Learning Engineer Nanodegree! In this notebook, some template code has already been provided for you, and it will be your job to implement the additional functionality necessary to successfully complete this project. Sections that begin with **'Implementation'** in the header indicate that the following block of code will require additional functionality which you must provide. Instructions will be provided for each section and the specifics of the implementation are marked in the code block with a `'TODO'` statement. Please be sure to read the instructions carefully!

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. In addition, Markdown cells can be edited by typically double-clicking the cell to enter edit mode.

Question 1 - Classification vs. Regression

Your goal for this project is to identify students who might need early intervention before they fail to graduate. Which type of supervised learning problem is this, classification or regression? Why?

Answer: This is a binary classification problem. We have to separate students into 2 classes, one is can success to graduate, and another one is fail to graduate. In other words, the outputs are YES or NO, not continuous numbers.

Exploring the Data

Run the code cell below to load necessary Python libraries and load the student data. Note that the last column from this dataset, `'passed'`, will be our target label (whether the student graduated or didn't graduate). All other columns are features about each student.

In [1]:

```
# Import libraries
import numpy as np
import pandas as pd
from time import time
from sklearn.metrics import f1_score

# Read student data
student_data = pd.read_csv("student-data.csv")
print "Student data read successfully!"
```

```
Student data read successfully!
```

Implementation: Data Exploration

Let's begin by investigating the dataset to determine how many students we have information on, and learn about the graduation rate among these students. In the code cell below, you will need to compute the following:

- The total number of students, `n_students`.
- The total number of features for each student, `n_features`.
- The number of those students who passed, `n_passed`.
- The number of those students who failed, `n_failed`.
- The graduation rate of the class, `grad_rate`, in percent (%).

In [2]:

```
# TODO: Calculate number of students
n_students = len(student_data)

# TODO: Calculate number of features
n_features = len(student_data.columns[:-1])

# TODO: Calculate passing students
n_passed = len(student_data[student_data.passed=='yes'])

# TODO: Calculate failing students
n_failed = len(student_data[student_data.passed=='no'])

# TODO: Calculate graduation rate
from __future__ import division
grad_rate = n_passed/n_students*100

# Print the results
print "Total number of students: {}".format(n_students)
print "Number of features: {}".format(n_features)
print "Number of students who passed: {}".format(n_passed)
print "Number of students who failed: {}".format(n_failed)
print "Graduation rate of the class: {:.2f}%".format(grad_rate)
```

```
Total number of students: 395
Number of features: 30
Number of students who passed: 265
Number of students who failed: 130
Graduation rate of the class: 67.09%
```

Preparing the Data

In this section, we will prepare the data for modeling, training and testing.

Identify feature and target columns

It is often the case that the data you obtain contains non-numeric features. This can be a problem, as most machine learning algorithms expect numeric data to perform computations with.

Run the code cell below to separate the student data into feature and target columns to see if any features are non-numeric.

In [3]:

```
# Extract feature columns
feature_cols = list(student_data.columns[:-1])

# Extract target column 'passed'
target_col = student_data.columns[-1]

# Show the list of columns
print "Feature columns:\n{}".format(feature_cols)
print "\nTarget column: {}".format(target_col)

# Separate the data into feature data and target data (X_all and y_all, respecti
vely)
X_all = student_data[feature_cols]
y_all = student_data[target_col]

# Show the feature information by printing the first five rows
print "\nFeature values:"
print X_all.head()
```

```
Feature columns:
['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'F
edu', 'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytim
e', 'failures', 'schoolsup', 'famsup', 'paid', 'activities', 'nurser
y', 'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout',
 'Dalc', 'Walc', 'health', 'absences']

Target column: passed

Feature values:
  school sex  age address famsize Pstatus  Medu  Fedu     Mjob
 Fjob  \
0     GP   F   18       U     GT3       A     4     4  at_home   tea
cher
1     GP   F   17       U     GT3       T     1     1  at_home     o
ther
2     GP   F   15       U     LE3       T     1     1  at_home     o
ther
3     GP   F   15       U     GT3       T     4     2   health  serv
ices
4     GP   F   16       U     GT3       T     3     3    other     o
ther

    ...    higher internet  romantic  famrel  freetime goout Dalc Wa
lc health  \
0   ...       yes       no        no       4         3     4    1
 1      3
1   ...       yes      yes        no       5         3     3    1
 1      3
2   ...       yes      yes        no       4         3     2    2
 3      3
3   ...       yes      yes       yes       3         2     2    1
 1      5
4   ...       yes       no        no       4         3     2    1
 2      5

  absences
0        6
1        4
2       10
3        2
4        4

[5 rows x 30 columns]
```

Preprocess Feature Columns

As you can see, there are several non-numeric columns that need to be converted! Many of them are simply `yes`/`no`, e.g. `internet`. These can be reasonably converted into `1`/`0` (binary) values.

Other columns, like `Mjob` and `Fjob`, have more than two values, and are known as *categorical variables*. The recommended way to handle such a column is to create as many columns as possible values (e.g. `Fjob_teacher`, `Fjob_other`, `Fjob_services`, etc.), and assign a `1` to one of them and `0` to all others.

These generated columns are sometimes called *dummy variables*, and we will use the [`pandas.get_dummies()` (http://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html?highlight=get_dummies#pandas.get_dummies)](http://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html?highlight=get_dummies#pandas.get_dummies) function to perform this transformation. Run the code cell below to perform the preprocessing routine discussed in this section.

In [4]:

```
def preprocess_features(X):
    ''' Preprocesses the student data and converts non-numeric binary variables
 into
        binary (0/1) variables. Converts categorical variables into dummy variab
les. '''

    # Initialize new output DataFrame
    output = pd.DataFrame(index = X.index)

    # Investigate each feature column for the data
    for col, col_data in X.iteritems():

        # If data type is non-numeric, replace all yes/no values with 1/0
        if col_data.dtype == object:
            col_data = col_data.replace(['yes', 'no'], [1, 0])

        # If data type is categorical, convert to dummy variables
        if col_data.dtype == object:
            # Example: 'school' => 'school_GP' and 'school_MS'
            col_data = pd.get_dummies(col_data, prefix = col)

        # Collect the revised columns
        output = output.join(col_data)

    return output

X_all = preprocess_features(X_all)
print "Processed feature columns ({} total features):\n{}".format(len(X_all.colu
mns), list(X_all.columns))
```

```
Processed feature columns (48 total features):
['school_GP', 'school_MS', 'sex_F', 'sex_M', 'age', 'address_R', 'ad
dress_U', 'famsize_GT3', 'famsize_LE3', 'Pstatus_A', 'Pstatus_T', 'M
edu', 'Fedu', 'Mjob_at_home', 'Mjob_health', 'Mjob_other', 'Mjob_ser
vices', 'Mjob_teacher', 'Fjob_at_home', 'Fjob_health', 'Fjob_other',
 'Fjob_services', 'Fjob_teacher', 'reason_course', 'reason_home', 'r
eason_other', 'reason_reputation', 'guardian_father', 'guardian_moth
er', 'guardian_other', 'traveltime', 'studytime', 'failures', 'schoo
lsup', 'famsup', 'paid', 'activities', 'nursery', 'higher', 'interne
t', 'romantic', 'famrel', 'freetime', 'goout', 'Dalc', 'Walc', 'heal
th', 'absences']
```

Implementation: Training and Testing Data Split

So far, we have converted all *categorical* features into numeric values. For the next step, we split the data (both features and corresponding labels) into training and test sets. In the following code cell below, you will need to implement the following:

- Randomly shuffle and split the data (`X_all`, `y_all`) into training and testing subsets.
  - Use 300 training points (approximately 75%) and 95 testing points (approximately 25%).
  - Set a `random_state` for the function(s) you use, if provided.
  - Store the results in `X_train`, `X_test`, `y_train`, and `y_test`.

In [5]:

```
# TODO: Import any additional functionality you may need here
from sklearn.cross_validation import train_test_split

# TODO: Set the number of training points
num_train = 300

# Set the number of testing points
num_test = X_all.shape[0] - num_train

test_size = num_test / (num_train+num_test)
#print test_size

# TODO: Shuffle and split the dataset into the number of training and testing po
ints above
X_train, X_test, y_train, y_test = train_test_split(X_all, y_all, test_size=test
_size, random_state=42)

# Show the results of the split
print "Training set has {} samples.".format(X_train.shape[0])
print "Testing set has {} samples.".format(X_test.shape[0])
```

```
Training set has 300 samples.
Testing set has 95 samples.
```

Training and Evaluating Models

In this section, you will choose 3 supervised learning models that are appropriate for this problem and available in `scikit-learn`. You will first discuss the reasoning behind choosing these three models by considering what you know about the data and each model's strengths and weaknesses. You will then fit the model to varying sizes of training data (100 data points, 200 data points, and 300 data points) and measure the F_1 score. You will need to produce three tables (one for each model) that shows the training set size, training time, prediction time, F_1 score on the training set, and F_1 score on the testing set.

The following supervised learning models are currently available in [`scikit-learn` (http://scikit-learn.org/stable/supervised_learning.html)](http://scikit-learn.org/stable/supervised_learning.html) **that you may choose from:**

- Gaussian Naive Bayes (GaussianNB)
- Decision Trees
- Ensemble Methods (Bagging, AdaBoost, Random Forest, Gradient Boosting)
- K-Nearest Neighbors (KNeighbors)
- Stochastic Gradient Descent (SGDC)
- Support Vector Machines (SVM)
- Logistic Regression

Question 2 - Model Application

List three supervised learning models that are appropriate for this problem. For each model chosen

- Describe one real-world application in industry where the model can be applied. *(You may need to do a small bit of research for this — give references!)*
- What are the strengths of the model; when does it perform well?
- What are the weaknesses of the model; when does it perform poorly?
- What makes this model a good candidate for the problem, given what you know about the data?

Answer:

- Gaussian Naive Bayes (GaussianNB)
  - application: spam filtering (identify spam e-mail)
  - strengths:
    - performs well with small data
    - training speed is fast
  - weaknesses:
    - zero frequency problem
    - conditional independence assumption
  - data: our data is small (395 samples)

- Decision Tree
  - application: purchase prediction (buy or not buy)
  - strengths:
    - training and prediction speed is fast
    - often perform well on imbalanced dataset
  - weaknesses:
    - likely overfit on data with a large number of features
  - data: our data is imbalanced (the ratio of pass and fail is 2:1)

- Support Vector Machines (SVM)
  - application: handwriting recognition
  - strengths:
    - effective in high dimensional spaces
    - power of flexibility from kernels
    - average predictive accurancy is higher
    - work well in complicated domains where there is a clear margin of separation
  - weaknesses:
    - large dataset requires high training time
    - don't work well with lots of noise.
  - data:
    - our data is imbalanced
    - our data is high dimensional

Setup

Run the code cell below to initialize three helper functions which you can use for training and testing the three supervised learning models you've chosen above. The functions are as follows:

- `train_classifier` - takes as input a classifier and training data and fits the classifier to the data.
- `predict_labels` - takes as input a fit classifier, features, and a target labeling and makes predictions using the F_1 score.
- `train_predict` - takes as input a classifier, and the training and testing data, and performs `train_clasifier` and `predict_labels`.
  - This function will report the F_1 score for both the training and testing data separately.

In [6]:

```
def train_classifier(clf, X_train, y_train):
    ''' Fits a classifier to the training data. '''

    # Start the clock, train the classifier, then stop the clock
    start = time()
    clf.fit(X_train, y_train)
    end = time()

    # Print the results
    print "Trained model in {:.4f} seconds".format(end - start)


def predict_labels(clf, features, target):
    ''' Makes predictions using a fit classifier based on F1 score. '''

    # Start the clock, make predictions, then stop the clock
    start = time()
    y_pred = clf.predict(features)
    end = time()

    # Print and return results
    print "Made predictions in {:.4f} seconds.".format(end - start)
    return f1_score(target.values, y_pred, pos_label='yes')


def train_predict(clf, X_train, y_train, X_test, y_test):
    ''' Train and predict using a classifer based on F1 score. '''

    # Indicate the classifier and the training set size
    print "Training a {} using a training set size of {}. . .".format(clf.__clas
s__.__name__, len(X_train))

    # Train the classifier
    train_classifier(clf, X_train, y_train)

    # Print the results of prediction for both training and testing
    print "F1 score for training set: {:.4f}.".format(predict_labels(clf, X_trai
n, y_train))
    print "F1 score for test set: {:.4f}.".format(predict_labels(clf, X_test, y_
test))
```

Implementation: Model Performance Metrics

With the predefined functions above, you will now import the three supervised learning models of your choice and run the `train_predict` function for each one. Remember that you will need to train and predict on each classifier for three different training set sizes: 100, 200, and 300. Hence, you should expect to have 9 different outputs below — 3 for each model using the varying training set sizes. In the following code cell, you will need to implement the following:

- Import the three supervised learning models you've discussed in the previous section.
- Initialize the three models and store them in `clf_A`, `clf_B`, and `clf_C`.
  - Use a `random_state` for each model you use, if provided.
  - **Note:** Use the default settings for each model — you will tune one specific model in a later section.
- Create the different training set sizes to be used to train each model.
  - *Do not reshuffle and resplit the data! The new training points should be drawn from `X_train` and `y_train`.*
- Fit each model with each training set size and make predictions on the test set (9 in total).
  Note: Three tables are provided after the following code cell which can be used to store your results.

In [7]:

```
# TODO: Import the three supervised learning models from sklearn
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC

rand = 42

# TODO: Initialize the three models
clf_A = GaussianNB()
clf_B = DecisionTreeClassifier(random_state=rand)
clf_C = SVC(random_state=rand)

# TODO: Set up the training set sizes

# TODO: Execute the 'train_predict' function for each classifier and each traini
ng set size
for clf in [clf_A, clf_B, clf_C]:
    for size in [100, 200, 300]:
        train_predict(clf, X_train[:size], y_train[:size], X_test, y_test)
        print '\n'
```

```
Training a GaussianNB using a training set size of 100. . .
Trained model in 0.0025 seconds
Made predictions in 0.0008 seconds.
F1 score for training set: 0.8467.
Made predictions in 0.0008 seconds.
F1 score for test set: 0.8029.


Training a GaussianNB using a training set size of 200. . .
Trained model in 0.0026 seconds
Made predictions in 0.0009 seconds.
F1 score for training set: 0.8406.
Made predictions in 0.0004 seconds.
F1 score for test set: 0.7244.


Training a GaussianNB using a training set size of 300. . .
Trained model in 0.0020 seconds
Made predictions in 0.0008 seconds.
F1 score for training set: 0.8038.
Made predictions in 0.0006 seconds.
F1 score for test set: 0.7634.


Training a DecisionTreeClassifier using a training set size of 100.
 . .
Trained model in 0.0017 seconds
Made predictions in 0.0004 seconds.
F1 score for training set: 1.0000.
Made predictions in 0.0002 seconds.
F1 score for test set: 0.6552.


Training a DecisionTreeClassifier using a training set size of 200.
 . .
Trained model in 0.0013 seconds
Made predictions in 0.0002 seconds.
F1 score for training set: 1.0000.
Made predictions in 0.0002 seconds.
F1 score for test set: 0.7500.


Training a DecisionTreeClassifier using a training set size of 300.
 . .
Trained model in 0.0022 seconds
Made predictions in 0.0003 seconds.
F1 score for training set: 1.0000.
Made predictions in 0.0002 seconds.
F1 score for test set: 0.6613.


Training a SVC using a training set size of 100. . .
Trained model in 0.0020 seconds
Made predictions in 0.0011 seconds.
F1 score for training set: 0.8777.
Made predictions in 0.0009 seconds.
F1 score for test set: 0.7746.


Training a SVC using a training set size of 200. . .
Trained model in 0.0038 seconds
```

```
Made predictions in 0.0025 seconds.
F1 score for training set: 0.8679.
Made predictions in 0.0013 seconds.
F1 score for test set: 0.7815.


Training a SVC using a training set size of 300. . .
Trained model in 0.0069 seconds
Made predictions in 0.0049 seconds.
F1 score for training set: 0.8761.
Made predictions in 0.0016 seconds.
F1 score for test set: 0.7838.
```

Tabular Results

Edit the cell below to see how a table can be designed in Markdown (https://github.com/adam-p/markdown-here/wiki/Markdown-Cheatsheet#tables). You can record your results from above in the tables provided.

Classifer 1 - GaussianNB

Training Set Size	Training Time	Prediction Time (test)	F1 Score (train)	F1 Score (test)
100	0.0025	0.0008	0.8467	0.8029
200	0.0026	0.0004	0.8406	0.7244
300	0.0020	0.0006	0.8038	0.7634

Classifer 2 - Decision Tree

Training Set Size	Training Time	Prediction Time (test)	F1 Score (train)	F1 Score (test)
100	0.0017	0.0002	1.0000	0.6552
200	0.0013	0.0002	1.0000	0.7500
300	0.0022	0.0002	1.0000	0.6613

Classifer 3 - SVM

Training Set Size	Training Time	Prediction Time (test)	F1 Score (train)	F1 Score (test)
100	0.0022	0.0009	0.8777	0.7746
200	0.0038	0.0013	0.8679	0.7815
300	0.0069	0.0016	0.8761	0.7838

Choosing the Best Model

In this final section, you will choose from the three supervised learning models the *best* model to use on the student data. You will then perform a grid search optimization for the model over the entire training set (`X_train` and `y_train`) by tuning at least one parameter to improve upon the untuned model's F_1 score.

Question 3 - Choosing the Best Model

Based on the experiments you performed earlier, in one to two paragraphs, explain to the board of supervisors what single model you chose as the best model. Which model is generally the most appropriate based on the available data, limited resources, cost, and performance?

Answer:

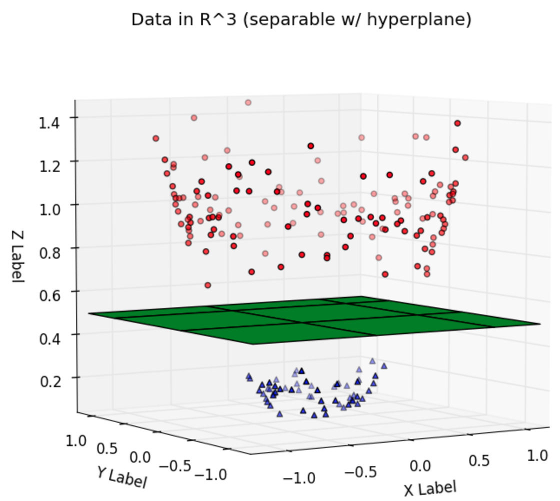
- I chose SVM as the best model.
- The highest priority is prediction accuracy. More accuracy, school can more effective to intervene dropouts. In many respects, we can save more education resources.
- Another considering point is system run time. School faulty would not operate the training and prediction precedures frequently. So we can compromise with poorly running time.
- Conclusion is that even the training and prediction times of SVM are more than the times of Naive Bayes and Decision Tree, but the F1 score is hightest among the three models. So SVM is the best choice.

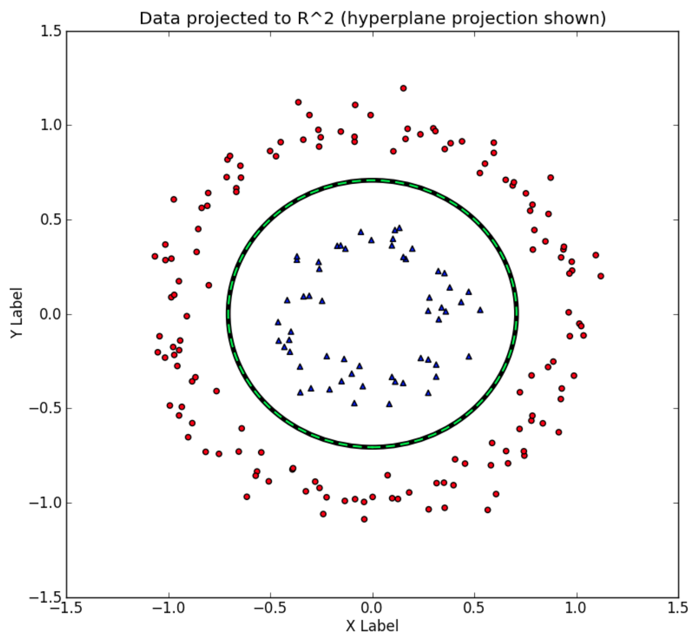
Question 4 - Model in Layman's Terms

In one to two paragraphs, explain to the board of directors in layman's terms how the final model chosen is supposed to work. Be sure that you are describing the major qualities of the model, such as how the model is trained and how the model makes a prediction. Avoid using advanced mathematical or technical jargon, such as describing equations or discussing the algorithm implementation.

Answer:

- What SVM(Support Vector Machines) do is to find a best separating line, or a hyperplane, between data of two classes. It's a line that maximizes the distance to the nearest points of either of the two classes, that distance is often called margin. The margin would be most robust to classification errors. On the other hand, if the line is close to existing data, then a small amount of noise would make the label flip and it is not robust. So the inside of svm is to maximize robustness of your result.
- What if there is just no good linear hyperplane or linear separator between the two classes? The answer is to use a method called kernal trick. We add new features(usually it's a equation) and we convert data from two-dimensional space(right graph) to three-dimensional space(left graph). And then we can find a hyperplane that separates two classes. (please refer right graph)





Implementation: Model Tuning

Fine tune the chosen model. Use grid search (`GridSearchCV`) with at least one important parameter tuned with at least 3 different values. You will need to use the entire training set for this. In the code cell below, you will need to implement the following:

- Import [`sklearn.grid_search.gridSearchCV` (http://scikit-learn.org/stable/modules/generated/sklearn.grid_search.GridSearchCV.html)](http://scikit-learn.org/stable/modules/generated/sklearn.grid_search.GridSearchCV.html) and [`sklearn.metrics.make_scorer` (http://scikit-learn.org/stable/modules/generated/sklearn.metrics.make_scorer.html)](http://scikit-learn.org/stable/modules/generated/sklearn.metrics.make_scorer.html).
- Create a dictionary of parameters you wish to tune for the chosen model.
  - Example: `parameters = {'parameter' : [list of values]}`.
- Initialize the classifier you've chosen and store it in `clf`.
- Create the F_1 scoring function using `make_scorer` and store it in `f1_scorer`.
  - Set the `pos_label` parameter to the correct value!
- Perform grid search on the classifier `clf` using `f1_scorer` as the scoring method, and store it in `grid_obj`.
- Fit the grid search object to the training data (`X_train`, `y_train`), and store it in `grid_obj`.

In [8]:

```
# TODO: Import 'GridSearchCV' and 'make_scorer'
from sklearn.grid_search import GridSearchCV
from sklearn.metrics import make_scorer
from sklearn.metrics import f1_score

# TODO: Create the parameters list you wish to tune
parameters = [
  {'C': [1, 10, 100, 1000], 'kernel': ['linear']},
  {'C': [1, 10, 100, 1000], 'gamma': [0.001, 0.0001], 'kernel': ['rbf']},
]

# TODO: Initialize the classifier
classifier = SVC(random_state=rand)

# TODO: Make an f1 scoring function using 'make_scorer'
f1_scorer = make_scorer(f1_score, pos_label="yes")

# TODO: Perform grid search on the classifier using the f1_scorer as the scoring
 method
grid_obj = GridSearchCV(classifier, parameters,scoring=f1_scorer)

# TODO: Fit the grid search object to the training data and find the optimal par
ameters
grid_obj = grid_obj.fit(X_train, y_train)

# Get the estimator
clf = grid_obj.best_estimator_

# Report the final F1 score for training and testing after parameter tuning
print "Tuned model has a training F1 score of
{:.4f}.".format(predict_labels(clf, X_train, y_train))
print "Tuned model has a testing F1 score of {:.4f}.".format(predict_labels(clf,
 X_test, y_test))
```

```
Made predictions in 0.0048 seconds.
Tuned model has a training F1 score of 0.8323.
Made predictions in 0.0015 seconds.
Tuned model has a testing F1 score of 0.7945.
```

Question 5 - Final F_1 Score

What is the final model's F_1 score for training and testing? How does that score compare to the untuned model?

Answer: The final F1 score is 0.7945. It is better than the score for untuned model.

> **Note**: Once you have completed all of the code implementations and successfully answered each question above, you may finalize your work by exporting the iPython Notebook as an HTML document. You can do this by using the menu above and navigating to
> **File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.